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MACHINE LEARNING TECHNIQUES FOR SELECTIVE LOGGING DETECTION IN X-BAND SAR IMAGES - A COMPARATIVE EVALUATION

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ABSTRACT

Land use, land use changes and forest degradation have historically been the sectors that most contribute to greenhouse gas emissions in Brazil, according to the System of Estimates of Greenhouse Gas Emissions and Removals (SEEG), degradation being the major contribution. Therefore, the necessary containment of the increase in emissions is closely related to the control and combat of deforestation and forest degradation. Given the contribution of logging activity in this scenario, monitoring it is an important part of ensuring that the market is selling only products originating from sustainable exploitation. This work compares three methodologies, based on machine learning, for the detection of selective logging in X-band SAR satellite images collected over the Amazon, a tropical region with persistent cloud cover throughout the year, justifying the use of SAR data for monitoring. The Convolutional Neural Networks tested showed good performance in detecting gaps resulting from exploration, with the U-Net architecture showing the best result (accuracy 97%) with the lowest pre-processing requirement, as it is a semantic segmentation approach, and not just classification, like the others.

Key words – *Selective logging, SAR, machine learning, Amazon forest, U-Net.*

1. INTRODUCTION

The Brazilian Amazon, housing at least 10% of the world's known biodiversity [1], is under constant threat due to the predatory exploitation of its natural resources. Timber is one of the products that supplies both the national and international markets, and its consumption has increased during the period of the COVID-19 pandemic. Despite the Brazilian government's tracking systems, part of the timber sold comes from illegally harvested areas [2].

Thus, it is necessary to improve the tracking systems of the entire timber chain, starting with the detection of its extraction. Brazil has advanced programs for monitoring deforestation and forest degradation [3], but still does not monitor selective logging with the frequency and level of detail necessary to quantify, at the national level, illegally extracted timber.

However, this monitoring is not a trivial task for the following reasons: 1) tropical regions have persistent cloud cover, limiting imaging with optical sensors; 2) the scars resulting from the extraction of a tree are small in relation to the scars resulting from other types of degradation and deforestation; 3) the volume of images needed to fully cover the Amazon biome at a spatial resolution that allows detecting the suppression of a tree would require a large computational capacity; 4) there are regional variations in floristic composition and atmospheric variations at each satellite convolution that result in spectral differences in optical images.

To overcome these limitations, this work proposes a method for detecting these features in SAR images operating in X-band, since these images suffer less interference from atmospheric variations and cloud cover than optical images, and interact with the canopy surface, where scars from tree suppression usually appear. Change detection based on machine learning techniques applied in SAR images has shown promising results [4]. Examples of these techniques are the Random Forest [5], AdaBoost [6], Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) [7] and the Convolutional Neural Network (CNN) [8]. In this study, we compared the performance of a simple CNN, a pre-trained CNN and U-Net for identifying selective logging activities in a forest concession site located in the Jamari National Forest, state of Rondônia, Brazil.

2. MATERIAL E METHODS

2.1. Study site

The study area is located in the Jamari National Forest (Jamari FLONA), state of Rondônia, in the municipalities of Cujubim, Candeias do Jamari and Itapoã do Oeste (Figure 1). The Flona is dominated by dense ombrophilous forest with portions of open ombrophilous forest, which may have a predominance of palm trees or lianas [9].

Jamari FLONA was created in 1984 and has approximately 220 thousand hectares, 96 thousand were destined for concession in 2008 [10]. Three companies have authorization from the Brazilian Forest Service to exploit the three forest management units existing in Flona (UMF I, II and III), and can exploit wood and other forest products such as latex, fruits and leaves. The UMF III, target of this study, is explored by the company Amata S/A, following the management criteria established by Brazilian legislation, considered, therefore, a low impact exploration. However, companies authorized to explore the area have been under pressure from the illegal logging that takes place in the southeast portion of the Flona,

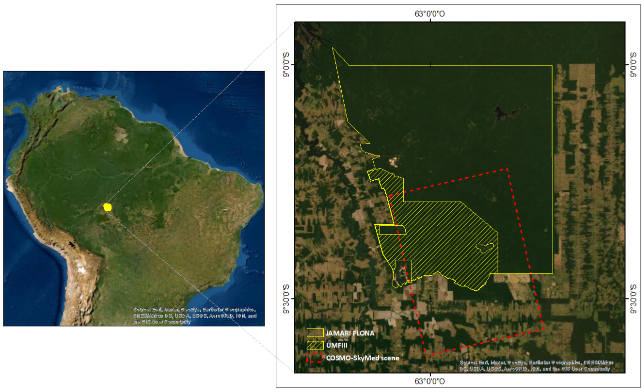

Figure 1: Study site

in the conventional way, causing greater impact.

The public notice for bidding for authorization to explore the FMUs includes the forest inventory, which includes the list of species that occur in the area. The forest inventory of Jamari FLONA was carried out by the Brazilian Institute for Forest Development (IBDF), in 1983, with the main purpose of subsidizing the process of creating the FLONA. The main objective of the forest inventory was to evaluate the productive potential of the forest, through estimates for the volume and number of trees of commercial species [10]. The choice of this area is due to the fact that, as it is an area of legal and controlled exploration, there is a large amount and variety of data on exploration.

2.2. Data

The SAR images used for selective logging detection come from the COSMO-SkyMed sensor, whose constellation includes 4 satellites operating in X band. Due to their short waves (approximately 3 cm), their interaction with the forest canopy is superficial. Two scenes acquired over the same area of the UMF III were used, at different times (before exploration and after exploration). The acquisition dates were January 8th (= 55th), June 5th (= 55o) and October 8th, 2018 (= 55o). The SAR images used were received in the single look complex (SLC) format and pre-processed before proceeding with the exploratory analysis. The pre-processing consists of converting the image to ground range image, filtering the speckle effect and generating the backscatter coefficient (o) [11]. The GammaMAP filter [12], with 3×3 window, was used to filter the speckle effect.

Two LiDAR images were used to select samples from selective wood extraction, which took place before and after logging, whose point clouds were processed to generate digital surface models, and the ratio between them allowed the identification of gaps resulting from the extraction. These gaps were confirmed by crossing them with georeferenced points from the inventory of extracted trees.

From the geocoded COSMO-SkyMed images of T1 (June/2018) and T2 (October/2018), we composed a RGB image with the coefficient of variation (output pixel value represents coefficient of variation between consecutive acquisition dates) in the red channel, minimum value (the output pixel represents the minimum value extracted from all input data) in the green channel, and the gradient (output pixel value represents the maximum absolute variation between consecutive acquisition dates) in blue channel.

2.3. Convolutional Neural Network Architectures

To detect the selective extraction features, 3 models of convolutional neural networks were tested: - Painters, that is a model trained in the dataset of the Painter by Numbers on Kaggle competition [13], consisting of 79,433 images of paintings by 1584 different painters, whose objective was to examine pairs of paintings, and determine if they are by the same artist. The network comprises a total of 24 layers; - A convolutional neural network with two 3×3 convolution layers with ReLU activation function and 2 and 6 feature maps, respectively, and two 2×2 pooling layers; - U-Net (Figure 2), designed in encoder-decoder form where it first follows a contracting path to obtain context information from the data and a symmetric expansion path for accurate location estimation [14]. It is also designed with jump connections that can speed up training and reduce data degradation by combining low-level details and contextual information [15]. According to [16] another advantage of U-Net is that it can train relatively good models on small datasets.

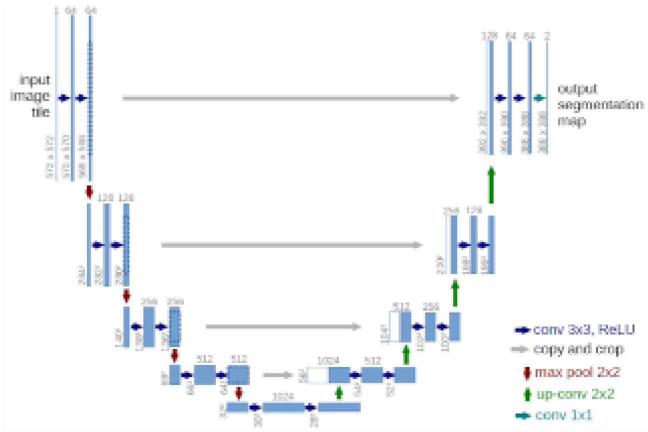

Figure 2: U-Net architecture [14]

Painters and traditional CNN networks were applied over the RGB composition described above. For this, we clipped sub-images of selective logging samples, true and false, previously labeled. U-Net was applied over the filtered COSMO-SkyMed backscattering images from June and October.

3. RESULTS

The subimages clipped by labeled polygons and classified by field truth were used as training (70%) and test (30%) sets, and the unlabeled ones to analyze the generalizability of CNN. Figure 3 shows a sample of the *covmingrad* images cut by these polygons.

The classification test by pre-trained CNN Painters on the *covmingrad* image presented an accuracy of 0.92, with a training and testing time of 124 and 1 seconds, respectively.

The generic CNN tested showed an accuracy of 0.90, having converged with 7 training epochs. One of CNN's requirements is that all images presented to the network have

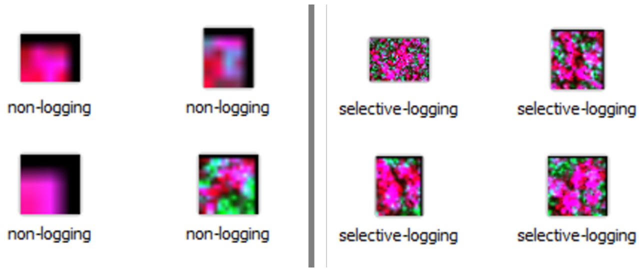

Figure 3: Examples of selective logging and non-logging covmingrad subimages

the same dimension. Therefore, it was necessary to resize the extraction and non-extraction samples to a 50×50 matrix (Figure 4). The Keras API [17], written in Python and used to run the CNN model, has the limitation of accepting as input only images in jpeg, png, bmp, gif. Thus, another necessary step was the conversion of the images, originally in .tif format with 16 bits, to jpeg format, with 8 bits, resulting in loss of radiometric information.

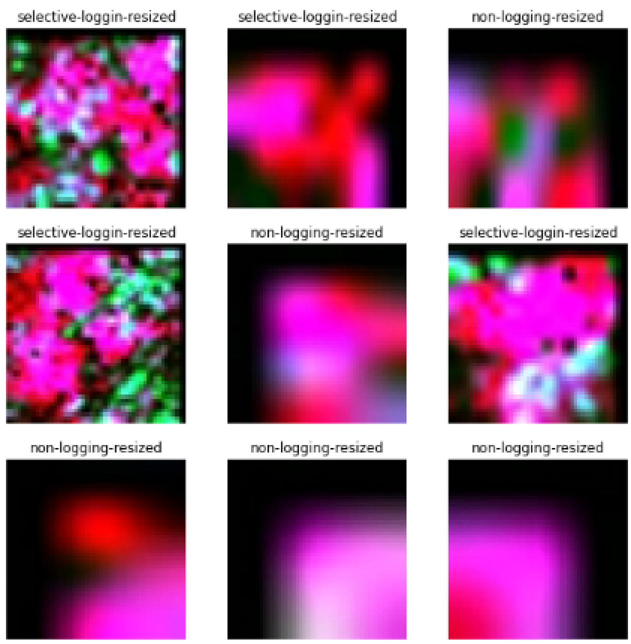

Figure 4: Examples of selective logging and non-logging *covmingrad* subimages resized for a CNN model

The U-Net results presented an accuracy of 0.9795 and an *intersection over union* (IoU) of 0.8097 for the test set. Figure 5 shows the network output in the fourth column from left to right, and it is possible to observe, in a qualitative way, that the inference obtained results very close to the field truth exposed in the third column.

4. DISCUSSION

Although all three approaches using convolutional neural networks have presented good results, it is important to note that the U-Net network, as it is based on semantic segmentation, and has the characteristic of recomposing the image in the decoder phase [14], requires less effort from the specialist with image pre-processing, since it is not necessary

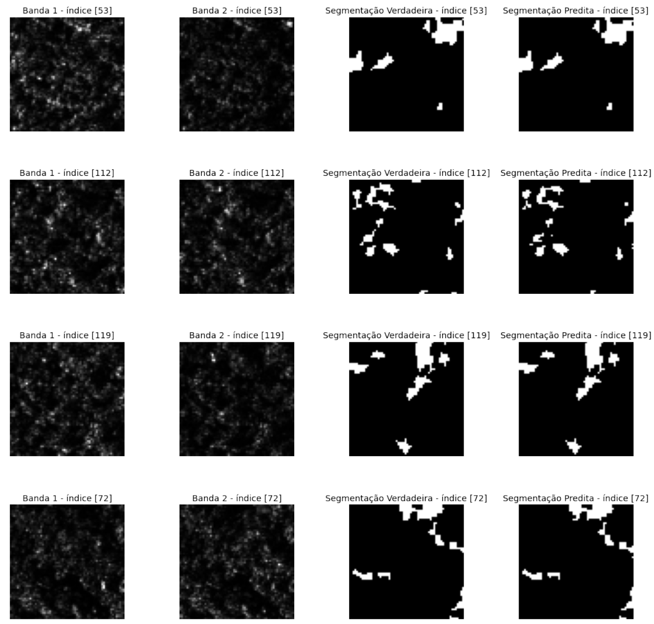

Figure 5: U-Net selective logging detections.

to select sub-images for classification, as in the case of other architectures.

A positive characteristic of the semantic segmenters is also attributed to the detection of feature geometry (Figure 5), which allows the dimensioning of the gap and consequently correlating this scar with the volume of extracted wood, as presented by [18].

The results were quite promising despite the sets (training and testing) not being considerably large. Interesting to see how the U-Net demonstrates good performance not only for optical images but also for SAR images. The semantic segmenters represent an evolution in relation to works presented by [19].

5. CONCLUSIONS

The images used in this study, whose acquisition dates coincided with the period before and after the selective logging at Jamari FLONA, allowed the identification of features resulting from this type of activity, since all images were acquired according to the same parameters (direction of the orbit, angle of incidence, band and polarization); therefore, temporal changes refer to changes in land cover rather than differences in acquisition parameters.

The present study represents an evolution of the study presented by [19], with the advantage that the convolutional network itself extracts the images attributes, eliminating the need for this step in the classification process. The reduction of stages is especially important when the objective is the systematic and operational monitoring of the entire Brazilian Amazon territory, which has an area larger than 5 million km^2.

The tests carried out showed that the approaches using convolutional neural networks present good performance for detecting changes in the forest canopy in X-band multitemporal SAR images, presenting an accuracy of 97% with the U-Net network. It is suggested that future studies explore the generalization capacity of this technique in environments with different floristic compositions and varying the parameters of acquisition of SAR images.

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